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Article

Exploration of Using an Artificial Intelligence-Assisted Adaptive Learning Platform to Enhance the Effect of Interactive Teaching in College English Classrooms

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Abstract: University English courses have poor classroom interaction due to the limitations of learning time and environment, so there is an urgent need to establish a benign teacher-student interaction. In this paper, based on the learning model of adaptive learning platform, a fuzzy neural network system is utilized to design the outline of adaptive learning platform. The theoretical model of teaching interaction is introduced, and the English adaptive learning platform based on ANFIS system is designed under the conceptual interaction, information interaction and operational interaction. Teaching interaction behaviors in the English classroom are analyzed, and the teacher-student verbal and behavioral rates of applying the adaptive learning platform for learning are comparable, basically staying at about 50%. Using the random survey method combined with pre and post-tests to measure the changes in students' experience of classroom interaction, after the implementation of the adaptive classroom, students' classroom experience changes significantly, students are interested in the English classroom, an increase of 31.43% compared with the previous, indicating that the implementation of the adaptive English learning platform, the classroom is welcomed by the students, and the effectiveness of the teaching and learning has been significantly improved.

Keywords: Adaptive Learning Platform; Fuzzy Neural Network System; Teaching Interaction Theory; English Classroom Interaction

1. Introduction

With the advancement of globalization, English has become the link between the people of the world, and mastering the ability of listening, speaking, reading and writing in English, as well as the proficiency of using English is also very necessary for college students [1-2]. However, there are many problems in the teaching process of college English, such as the single traditional teaching method and the lack of interest of many students in learning English, which makes whether college students can master English or not a difficult problem in college English teaching today [3]. In recent years, the development of Internet information technology has been accelerating, with more and more intelligent learning platforms, and smart phones and computers have become essential learning tools for students [4]. Applying the Internet to learn has gradually become a common way of learning among contemporary college students, and students can utilize intelligent learning platforms to learn on their own in order to improve their learning ability [5-6].

In the era of artificial intelligence, the traditional college English teaching mode is beginning to change, and teachers are no longer focusing on the traditional classroom teaching mode to instill knowledge in students. Instead, they utilize the intelligent learning platform as a teaching aid for teaching, and students can learn anytime and anywhere through the platform, which makes the students' motivation and interest in learning fully mobilized. By utilizing the intelligent learning platform,

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students are also able to take advantage of the leisure time in their lives to expand the scope of independent learning of English [7]. The introduction of intelligent technology brings new opportunities for the traditional English classroom interaction mode, which can break through the time and space limitations, create a real language environment and provide personalized learning support [8-9]. Constructing a new mode of classroom interaction supported by intelligent technology is of great significance for improving teaching quality and cultivating compound talents [10].

It is essential to integrate university English teaching with smart learning platforms. Earlier, Mokhtar et al. (2015) pointed out that Edmodo intelligent English learning platform can provide a more suitable English learning environment for students, and its attached classroom interaction function advances students' active learning, which can provide students with a unique English learning experience [11]. And in recent years, there are more and more researches on intelligent English education.Tang et al. (2021) improved the English learning platform by embedding a neural network model in the platform to simulate the learning mode of English learners, so that students can become the main body of the classroom, which stimulates the students' interest in English learning [12]. Sun et al. (2021) established an artificial intelligence-driven online intelligent English learning system to assist students in personalized learning according to the degree of knowledge mastery, and at the same time evaluate the English learning situation based on decision tree technology, which further improves the interactivity and teaching effect in the classroom [13]. Wu et al. (2023) analyzed the impact of teacher-student interactive learning platform based on "resource-platform-demand" on learners' English learning through the data-driven approach, and analyzed the effect of the "resource-platform-demand" on learners' English learning, and the impact on students' English learning. Wu et al. (2023) analyzed the impact of a "resource-platform-needs" based teacher-student interactive learning platform on learners' English learning through a data-driven approach, which has significant implications for the design and optimization of online interactive platforms for English education [14]. Aprianto et al.'s (2024) study revealed the association between intelligent learning platforms and learners' learning intensity, and they found that platforms such as quizzes, discussion forums, interactive assignments, gamification, constructive feedback, collaboration, intuitive interface design, and diverse learning materials are important for improving learning. diverse learning materials play an important role in improving learning intensity [15]. Liu (2024) collected and analyzed learners' historical learning data through a social network learning platform to construct a user profile of learners, and the results of the study showed that the platform's personalized recommendations and social functions promoted interaction between learners and enhanced learning effectiveness [16].

In the university English classroom supported by intelligent technology, there are still some urgent problems to be solved. For example, the disconnection between technology application and teaching objectives and the imperfection of the interactive effect evaluation system, uneven student participation and other problems constrain the improvement of teaching effect [17-18]. The emergence of these problems reflects the reality of the dilemma of intelligent technology in the process of teaching and learning application, which needs to be solved through systematic optimization measures to promote the organic integration of intelligent technology and classroom teaching.

In this paper, starting from the learning process of adaptive learning platform, with the support of artificial intelligence, we propose an adaptive learning model that contains four aspects: comprehensive learning, targeted learning, quiz, and result feedback. By integrating fuzzy logic and artificial neural network, a fuzzy neural network system is constructed layer by layer, and the model is self-adaptive by continuously adjusting the parameters. The model is used to design the outline of the adaptive learning platform, construct the conceptual model of teaching interaction, and complete the teaching interaction design of the adaptive learning platform. The model is applied in practice, and students from University of T are selected to conduct pre- and post-test experiments to evaluate the interactive effect of the adaptive learning platform through the interactive behavior matrix of classroom teaching and feedback of teaching effect.

2. Adaptive learning based on artificial intelligence assistance

2.1. Adaptive learning model supported by artificial intelligence technology

2.1.1. Comprehensive learning

The adaptive learning platform learning process is shown in Figure 1 [19]. The adaptive learning platform utilizes movies and documents instead of classes, and the platform's practice system records the learner's practice records, allowing the learner to move from school to home and from home to school.

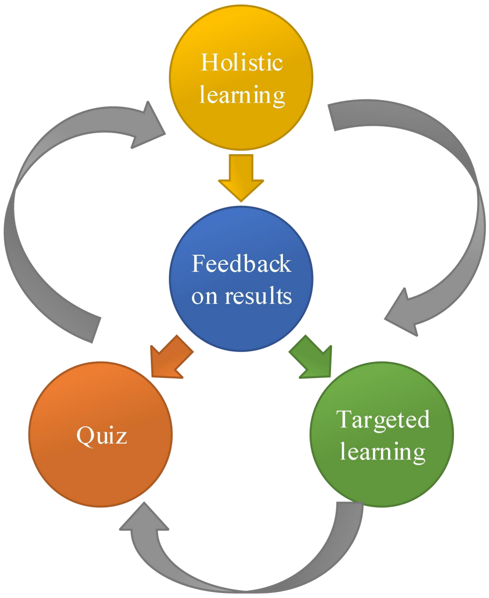

Figure 1. Adaptive learning platform learning process 4

Adaptive learning platform learners according to their own needs to select the knowledge points to learn, after learning the system will be the user profile, to lay the foundation for the subsequent knowledge points pushed.

2.1.2. Targeted learning

The platform system will analyze the data according to the learners' questions and push the relevant learning materials for weak knowledge points to the learners, which are mostly presented in the form of text, video or pictures, and belong to the explanatory and supplementary materials. Learners use these explanatory materials to further consolidate their weak knowledge points, and this "symptomatic" learning method effectively avoids repeating questions and does not waste learners' limited learning time, thus improving learning efficiency.

2.1.3. Tests

The quiz section in the Adaptive Learning Platform has a summary quiz as well as a unit quiz. After learning a point, the learner has the option of completing a summary quiz, which is specific to the content of a particular point. The unit quiz is a summary test that covers all the knowledge points of the unit. Both tests have the function of timely feedback. Whenever the learner finishes a topic, the system will give the learner a result. If the learner makes a mistake in a topic, the system will prompt "Get Help" and "Use Hints", and after clicking on them, there are the solutions to the topic. Ideas. After completing the test, there will be a rough summary, which serves to quantify the results of each test.

2.1.4. Feedback on results

The result feedback is the system platform on the learner's learning situation is summarized, according to the learner's results of the questions, to analyze the learner's mastery of each knowledge point. The learner can carry out targeted learning according to the system's tips or comments, checking for gaps, not only to avoid repeating questions, but also to fully consolidate the knowledge points.

These four links are cyclic iteration, the results of each link will affect the generation of the next step, the learner learning status of timely feedback mechanism to strengthen the learner's memory of the knowledge points, to avoid the short-term memory caused by the drawbacks.

2.2. Application of Fuzzy Neural Networks in English Adaptive Learning

2.2.1. Fuzzy Logic Principles and Fuzzy Inference Systems

(1) Principles of fuzzy logic

Fuzzy sets are the basis of fuzzy logic, and to understand the concept of fuzzy sets it is first necessary to understand the traditional classical sets [20]. In classical binary logic, a proposition can be true or false, and no other proposition exists between true and false propositions. This concept was introduced at the end of the 19th century, where the authors argued that the whole of things that are determinate, distinct, and different in a domain with certain properties is called a set, and the elements that make up the set are called its elements or meta. However, classical logic shows that its determination of right and wrong cannot help us to solve fuzzy problems and phenomena, therefore, the concept of fuzzy sets emerged to solve the problem of not being able to accurately determine whether an element belongs to a set or not, defined as follows.

Given an argument domain X, X is the set of objects generally denoted by x, then a fuzzy set is represented as in equation (1):

$$\tilde{A} = \left\{ \left(x, \mu_{\tilde{A}}(x) \mid x \in X \right) \right\} \tag{1}$$

where $\tilde{A}$ denotes a fuzzy subset, that is, a fuzzy set, on the domain X, and $\mu_{\tilde{A}}$ denotes the affiliation function of $\tilde{A}$. For each $x \in X, \mu_{\tilde{A}}(x)$ denotes the degree of affiliation of the element x to $\tilde{A}$, and its value ranges from the closed interval $[0,1]$, when the value of $\mu_{\tilde{A}}(x)$ is closer to 1, it indicates that the degree of x affiliation to $\tilde{A}$ to a greater extent, and if the value of $\mu_{\tilde{A}}(x)$ is closer to 0, it indicates that x is subordinate to $\tilde{A}$ to a lesser extent.

Then the fuzzy rules associated with it need to be established. The most commonly used fuzzy rules are Mamdani fuzzy rules and Taskagi-Sugeno-Kang fuzzy rules, which are introduced next.

Mamdani fuzzy rules are usually used to express inference patterns that are not precise enough, and their rules are expressed in the following form:

R_l: IF x_1 is A_1^l and $\cdots$ and x_n is A_n^l

$$\text{THEN } y_1 \text{ is } B_1^l \text{ and } y_m \text{ is } B_m^l, l = 1, 2, \cdots, r \tag{2}$$

Where R_l denotes the l th fuzzy rule, r is the number of fuzzy rules, and A_n^l and B_m^l are fuzzy sets of inputs x_n and outputs y_m. Among them, the antecedent in the rule, that is, A_n^l and the consequent B_m^l are fuzzy linguistic variables, and its input quantity and output quantity are fuzzy data, but generally the output of the consequent requires a clear quantity of data, as expressed in the following equations, and the consequent B_m^l usually adopts a single-point fuzzy set, and the rule is as follows:

$$R_l: \text{IF } x_1 \text{ is } A_1^l \text{ and } \cdots \text{ and } x_n \text{ is } A_n^l, \text{THEN } y_m \text{ is } C \tag{3}$$

Where C is the clarity value, which is the single point fuzzy set. Since the fuzzy rule generally used for Mamdani fuzzy rule is generally fuzzy in its posterior, it tends to be used for fuzzy inference systems with low complexity and not too demanding.

Taskagi-Sugeno-Kang fuzzy rule is a fuzzy rule proposed by Taskagi and Sugeno, which is different from the Mamdani fuzzy rule in that its posterior is a clear value, and its rule expression is as follows:

R_l: IF x_1 is A_1^l and $\cdots$ and x_n is A_n^l

$$\text{THEN } y_l = m_0^l + m_0^l x_1 + \cdots + m_n^l x_n, l = 1, 2, \cdots, r \tag{4}$$

where R_l denotes the l th fuzzy rule, r is the number of fuzzy rules, A_n^l is the fuzzy set of inputs x_n, m_n^l is a real-valued parameter, $x = \left[x_1, x_2, \ldots, x_n \right]^T$ is the input vector and y_l is the output of the l rule, whose posterior is represented by a function of the fuzzy inputs, and which has the advantage of avoiding unnecessary complexity in computation since its total output is obtained by weighted averaging.

(2) Fuzzy inference system

Fuzzy inference system is also known as fuzzy rule system, fuzzy expert system, fuzzy associative memory system, fuzzy controller, fuzzy model or simple fuzzy system. It mainly consists of four modules, fuzzy inference system is shown in Fig. 2, which are fuzzification, fuzzy inference machine, knowledge base and defuzzification.

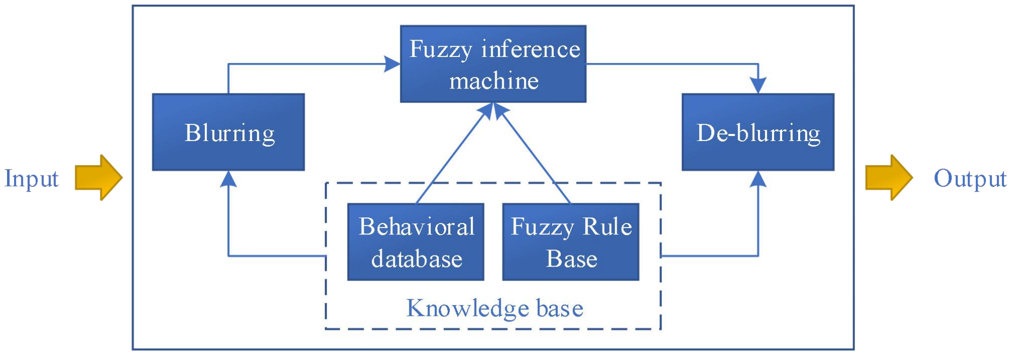

Figure 2. Fuzzy logic system

2.2.2. Artificial Neural Network Principles and Classical Models

(1) Principle of Artificial Neural Network

For artificial neural network, it is also composed of one artificial neuron, which tries to replicate the structure and behavior of natural neurons, and its neurons are composed of three parts, namely, connection weights, summation units and activation functions.

(2) Classical model of neural network

This study focuses on analyzing two neural network models, Hopfield neural network, which is typical of feed-forward neural networks and feedback neural networks, from the difference in the connection methods of neural networks.

The Hopfield neural network is higher than the BP neural network in terms of stability, while the connection right established by the Hebb learning rule it uses gives it the characteristic of rapid convergence [21]. Its structure consists of a two-dimensional connected neural network where each neuron is connected to all other neurons except itself, which avoids permanent feedback on its own state.

2.2.3. Fuzzy Neural Network Systems

The current research on hybrid fuzzy neural networks is less and less mature, so this study focuses on one of the more typical fuzzy neural networks and neuro-fuzzy system models.

T-S fuzzy neural network consists of two parts, respectively, the antecedent network and the posterior network, the antecedent network is used to match the input of fuzzy rules, and the posterior network is used to generate the output of fuzzy rules. There are four layers in the antecedent network, the first layer is the input layer, the second layer is the fuzzy set of inputs, each fuzzy set has multiple nodes, these nodes are the linguistic values of this fuzzy set, and its function is to find the size of the affiliation function of each linguistic value corresponding to the inputs, and the second layer computes the expression as follows if the affiliation function used is bell-shaped:

$$\mu_i^j = \mu_{A_i^j}\left(x_i\right) = e^{-\frac{\left(x_i - c_{ij}\right)^2}{\sigma_{ij}^2}}, i = 1,2,\cdots,n; j = 1,2,\cdots,m_i \quad (5)$$

μ_i^j is the affiliation function, n is the dimension of the inputs, m_i is the number of fuzzy partitions of x_i, c_{ij} is the center of the affiliation function and σ_{ij}^2 is the width of the affiliation function. The third layer is the fuzzy rule base, in which each node is a fuzzy rule, this part is mainly to calculate the weight of each fuzzy rule, there are two ways of calculating the weight of fuzzy rules, the first is to take the minimum of the value of the affiliation function of the antecedent, and the second is to multiply the values of the affiliation function of the antecedent. The number of nodes in the fourth layer is the same as that in the third layer, and the purpose is for performing normalization calculations.

The first layer of ANFIS system is the fuzzification layer, x and y are the inputs of the nodes in this layer, A_i and B_i are the fuzzy sets associated with the nodes, the function of this layer is to fuzzify the inputs and the output is the antecedent's degree of affiliation, and the output function of node i is:

$$O_i^1 = \mu_{A_i}(x) \text{ or } \mu_{B_i}(x), i = 1,2 \tag{6}$$

The second layer is the rule inference layer, the nodes in this layer are fixed nodes identified as II, which are parameterless, and its output is the product of the values of the affiliation functions of the output of the first layer, and the magnitude of the product represents the degree of activation of each rule, with the following expression:

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), i = 1,2 \tag{7}$$

Where A_i and B_i are the fuzzy sets in the first layer, μ_{A_i} and μ_{B_i} are the affiliations of the fuzzy set's affiliation function, and the rule strengths O_i^2 is the product of the affiliations.

The third layer is the intensity normalization layer, the nodes in this layer are fixed nodes identified as N. The output of this layer is the ratio of the activation intensity of each rule to the activation intensity of all the rules, and the main function is to normalize the activation intensities, and the arithmetic expression of this layer is as follows:

$$O_i^3 = \overline{w}_i = \frac{w_i}{\left(w_1 + w_2\right)}, i = 1,2 \tag{8}$$

The fourth layer is the defuzzification layer, each node in this layer is an adaptive node and the output of the fourth layer is:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i \left(p_i x + q_i y + r_i\right), i = 1,2 \tag{9}$$

Where $\overline{w}_i$ is the output of the third layer, p_i, q_i and r_i are the parameters and they are uniformly referred to as the conclusion parameters.

The fifth layer is the output layer, the nodes in this layer are fixed nodes identified as Σ, and the total output value of each input signal is calculated by using a weighted average with the following expression:

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{10}$$

Such five layers can simply constitute an adaptive neuro-fuzzy system that can realize self-adaptation by continuously adjusting the parameters.

2.3. Adaptive Learning Platform Outline Design

2.3.1. Overall Entity Relationships for the English Adaptive Learning Platform

Using the adaptive neuro-fuzzy system composed above, design the adaptive learning platform. According to the requirement analysis, we know that the main entities of the English learning platform are: students, teachers, learning resources, test questions, test papers, etc., and analyze to get their main attributes. According to the relationship between these entities, the entity relationship diagram of English learning platform is drawn. According to the entity relationship diagram, detailed analysis and design, the use of object-oriented design ideas, according to the system requirements analysis, English learning platform for class abstraction.

2.3.2. Calculation of student aptitude tests

The construction of the English learning platform actually uses computers to provide students with resources for learning and to control the content and process of their learning, with a focus on the use of computers to achieve adaptive testing to better grasp the learning of learning.

The stage of accurate assessment of students' abilities. After obtaining information about the initial ability level of the testee, further precise estimation of his/her ability level is needed based on this in order to correct the results obtained in the initial assessment stage. The general approach used is to design a scientifically sound selection strategy until the test requirements are met.

The algorithms used in the initial assessment of students' abilities include the step method and the logarithmic ratio method. The step method is relatively simple, mainly based on the students' actual answers to the questions, according to a certain step to increase or decrease the current assessment value. The logarithmic ratio method is to use the natural logarithm of the ratio of the number of correct answers to the number of incorrect answers as the ability value of the tester after the end of this test. The specific formula of the algorithm is shown in equation (11):

$$\hat{\theta} = \begin{cases} \ln \dfrac{t_r}{t_w} & t_r, t_w \text{ are not equal to 0} \\ \ln \dfrac{t_r + 0.5}{t_w + 0.5} & t_r, t_w \text{ has a value equal to 0} \end{cases} \tag{11}$$

2.3.3. Selection Strategy Modeling and Implementation

Many strategy models have emerged in the application of adaptive topic selection, such as the maximum information method, the ability matching method, and the topic selection strategy with a, b, c three types of parameters. Each of these methods has its own characteristics, but they also have drawbacks, such as not being able to provide better control in terms of topic exposure and content balance. Therefore, it is necessary to improve them.

The results of the adaptive selection strategy for test questions have their own criteria for judging, mainly including the following aspects:

(1) Reliability criterion. The reliability criterion is the evaluation criterion that the test question selection strategy plays a role in inferring the ability of the test subject, and the strategy with high reliability is able to infer the ability of the test subject more accurately.

(2) Accuracy criterion. The accuracy criterion is used to measure the deviation between the test taker's ability inferred from the test questions and his/her own true ability, and is generally calculated by using the mean deviation and the mean square deviation.

(3) Exposure criteria. The exposure rate criterion is calculated as the number of times any one question is used in all tests, compared to the number of people taking the test; the higher the exposure rate, the higher the risk that the test question will be known by the enhancement, and if the exposure rate is too small, the lower the utilization rate of the test question resources.

(4) Indicator of distribution of question exposure. Ideally, the questions in the question bank should be distributed evenly across the tests, thus increasing the utilization rate of the question bank. Let the total number of test questions be N and the length of the test L. The metric x^2 used to measure the exposure distribution is calculated as:

$$x^2 = \sum_{j=1}^{N} \frac{\left(er_j - L/N\right)^2}{L/N} \tag{12}$$

Where er_j is the exposure of the j th question obtained statistically during the actual application. The smaller the value of x^2, the higher the utilization rate of the question bank.

The topic selection strategy studied in this research is mainly used to solve the problem of balancing the exposure of test questions and the content of test questions. The basic solution idea is based on the strategy of hierarchical question selection, the introduction of the SympsonHetter method to solve the problem of exposure rate, and the improvement of the polynomial model to solve the problem of content balancing.

The improved polynomial model for content balancing is mainly based on first forming a cumulative distribution based on the target proportion of content domains, combining with random numbers conforming to a uniform distribution, generating a content domain to be selected, and finally selecting a question. When a content domain reaches the target, then the content domain is rebalanced.

Figure 3 shows the test question processing flow and Figure 4 shows the question selection process flow. Firstly, the question selection strategy stratified by C is improved by introducing the polynomial model. To effectively solve the content balance problem, and then introduce the SympsonHetter algorithm test question exposure control. The specific processing flow is as follows:

1) Set the maximum exposure rate. Set the maximum exposure of the j th item to r_j , with a general value set to 0.2-0.3.

2) Perform SympsonHetter iterations for each item to obtain its exposure parameters. The exposure parameters are mainly obtained by simulating the implementation of the test, remember the probability that the j item is selected as $P\left(\mathrm{S}_j\right)$, and the probability that the item is an implementation as $P\left(\mathrm{A}_j\right)$, then if $P\left(\mathrm{A}_j\right) > r_j$, then the exposure of the project is $r_j / P\left(\mathrm{S}_j\right)$, otherwise, the control parameter is 1.

3) Generate a cumulative target distribution with a target scale sum of 1.0.

4) Group the questions according to the knowledge points contained in the content, noting the number of groups as G.

5) Test questions are ranked in ascending order of difficulty. Based on the difficulty value b in the item response model, the questions in each group are ranked in ascending order of difficulty.

6) Groups are partitioned by difficulty. For the gth group, the test questions in it are divided into P_g regions, and the regions are arranged sequentially, with the questions in the first region having the lowest difficulty and the questions in the last region having the highest difficulty.

7) Ascending order of test question differentiation. Arrange the items in P_g according to the differentiation a.

8) Stratification by Distinctiveness a within the region. Divide the items in P_g into k strata.

9) Merge hierarchies. All kth levels in each group are merged and the final question bank forms k levels.

10) Adjust the testing process into k stages to match the kth level in the question bank.

11) For each test phase, the process is performed using a modified polynomial modeling approach, i.e., for the k th phase, a difficulty coefficient matching P_g partition matching the current content region, where the test questions that are closest to the test taker's ability are in the current region, are selected and the kth level of them is visited.

12) Control the exposure of the questions using random numbers. The random number should obey a uniform distribution $U(0,1)$, which is compared to the exposure of the selected topic, and if the value of the exposure control parameter is greater than the random number, the item is implemented: otherwise, the next ability value is compared to the item that is closest to the current valuation of the ability of the person being tested for judgment until a topic is available for selection.

13) Repeat steps 11 through 12 until the test is complete.

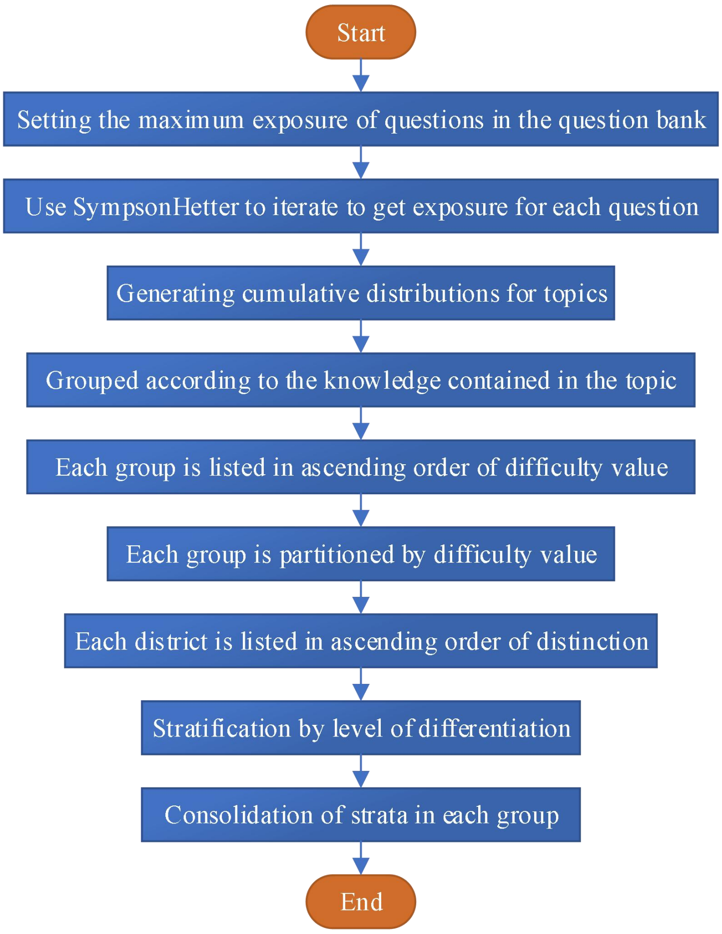

Figure 3. Test question processing procedure

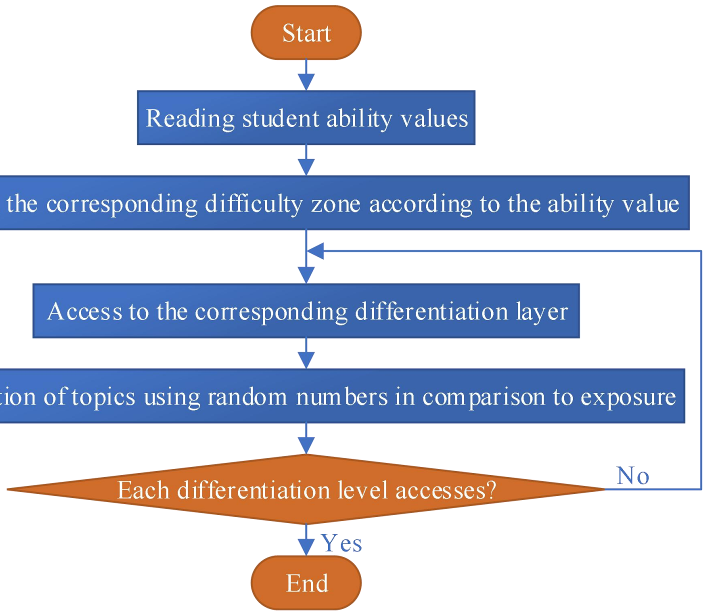

Figure 4. The process flow of topic selection

This topic selection strategy combines the advantages of the three methods of stratification strategy by C, SympsonHetter method, and improved polynomial model, using the stratification method to make the content of each layer as balanced as possible with the content and difficulty system of the question bank, and to achieve an orderly increment in the differentiation degree of the questions, and dividing the whole process of testing into multiple stages, which gives play to the advantage of stratification algorithm to prioritize the use of low differentiation degree questions. Advantage: then the SympsonHetter algorithm and the improved polynomial model are respectively utilized to effectively control the exposure and content balance of the items using random numbers to achieve the expected results.

3. English Adaptive Learning Platform Construction

3.1. A Theoretical Model of Instructional Interaction for Adaptive Learning Platforms

3.1.1. Theoretical Model of Instructional Interaction

Teaching interaction generally refers to all teaching scenarios, the meaningful interaction behavior between the participating subjects, it is a special interaction mode, so it follows the three elements of interaction behavior - interaction subject, interaction, interaction effect, interaction impact. The core interaction subjects of teaching interaction in adaptive learning scenarios are students, teachers and other students, adaptive learning platforms, and learning resources. Interaction and interaction effect are interconnected and mutually causal, and interaction effect is the change between interaction subjects through interaction, so the two are jointly called "interaction behavior and effect" when constructing the model, and the interaction subject and interaction behavior and effect are the core elements and the basic logic of the research in this section.

3.1.2. Interaction of adaptive learning platforms

(1) Conceptual interaction

Conceptual interaction is the core and goal of teaching interaction, conceptual interaction is the most top-level and high-level interaction in teaching interaction, and "concepts" are all the contents that can be involved in the interaction, which may be knowledge, or mental state, habits, interests, etc. Conceptual interaction reflects the change process and results of learners' cognitive level. Conceptual interaction reflects the change process and results of the learner's cognitive level, and objectively reflects the learner's teaching goals and learning effects.

(2) Information interaction

According to the hierarchical tower model of teaching interaction, information interaction is divided into three aspects: the interaction between students and teachers, the interaction between students and other students, and the interaction between students and learning resources, which are divided according to the interaction objects, and strictly speaking, there are intersections between these three types of interaction. The essence of information interaction is a process of knowledge construction. Knowledge construction is the core term of constructivist learning theory, which refers to the process and result of the learner completing the interaction of old and new knowledge through learning tasks, so that new meaningful associations, combinations, or unifications are produced among knowledge. The way of knowledge construction is divided into two categories, one is the construction of individual learners, i.e., learners produce the process of knowledge updating in their brains autonomously through interaction with learning resources, and the second is the production of new knowledge by learners through contacting and communicating with other learners and teachers, etc., which generates knowledge interaction.

(3) Operational interaction

In the traditional teaching mode, the media of operational interaction is mainly textbooks, and the interaction behavior of students is turning the pages of the book, and the learning of this operational interaction behavior has a lower cost and a smaller impact on the learning effect. However, under the background of adaptive learning, the traditional teaching mode has been changed, emphasizing students' autonomy and interactivity, which also puts forward higher requirements for the interactive design of learning media, and the simple and easy-to-learn operational interaction not only helps to improve students' experience, but also effectively improves the learning effect.

3.2. Instructional Interaction Design for Adaptive Learning Platforms

(1) Teaching preparation

Teaching preparation is the beginning of the whole teaching process, in the adaptive learning scenario, product designers first need to analyze the needs of the audience, clarify the teaching objectives, lay a theoretical foundation for the implementation of teaching, and in the preparation of teaching resources, they need to design the knowledge mapping according to the characteristics of knowledge, and connect the whole learning process with appropriate content and forms to improve the teaching effect and enhance the learning experience.

(2) Teaching Implementation

Teaching implementation in adaptive learning scenarios is actually a process in which learners learn independently through the platform and plan their next learning program under the guidance of the platform and teachers. Combining the process design of traditional teaching and the characteristics of the adaptive learning platform, the authors divide the teaching implementation into four stages: the first step is to guide the learners to use the learning tool to understand the current learning situation and learning content, the second step is to make the learners understand the key points of knowledge through the learning of the basics, and the third step is the advanced step of the second step, and after the completion of the learning of the basics and variants of the content of each knowledge point, the platform will examine the learners through the Comprehensive test questions to examine the application of knowledge of the learners, and the fourth step is testing and evaluation, which examines the knowledge mastery of the learners in stages, checks the omissions and makes up for the deficiencies, and plans the next step of the learning program.

(3) Teaching feedback

Traditional teaching usually takes extracurricular assignments as teaching feedback, and teachers judge learners' knowledge mastery through their assignments and arrange learning plans, which has the disadvantages of unidirectionality and one-sidedness. Adaptive learning platform helps teachers to get rid of the pressure of homework correction, and through data tracking and analysis, it provides a perfect and scientific learning report for teaching, which helps teachers to adjust teaching strategies in time. In addition, teaching feedback also needs to include teaching interaction and teaching evaluation, providing learners with the opportunity to ask questions and communicate actively, and supplementing the evaluation of learners and teachers on the teaching content, product use and other aspects.

4. Effectiveness of English Interactive Teaching Based on Adaptive Learning Platforms

4.1. Interactive Behavior in English Classroom Teaching

4.1.1. Behavioral matrix analysis of classroom teaching interactions

Figure 5 shows the interactive behaviors of college English classroom, the resources are from college English classroom videos, 4 sections are teaching videos using the adaptive learning platform constructed in this paper including 2 sections of lower grade (freshman year) and 2 sections of upper grade (junior year), numbered as SC1-SC4.The remaining 4 sections are teaching videos of traditional English classroom including 2 sections of lower grade (freshman year) and 2 sections of upper grade (junior year) which are numbered TMC1-TMC4.

The teacher-student speech and behavior rates from SC1 to SC4 are comparable, basically remaining at about 50%, and the gap between the teacher-student speech and behavior rates from MC1 to TMC4 is larger, about 60%:40%. It shows that a biased teaching structure is easy to be formed in the traditional English classroom. In addition to interpersonal interaction, there is also human-computer interaction and frequent interaction on the Adaptive Learning Platform, which can mobilize the enthusiasm and initiative of students' interaction, and it is easy to form the teaching structure of "teacher-led and student-led". Comparing the speech and behavior rates of teachers and students in high and low grades, no significant changes were found, indicating that grade level basically does not have a significant impact on the teaching structure, which is more influenced by the teaching environment.

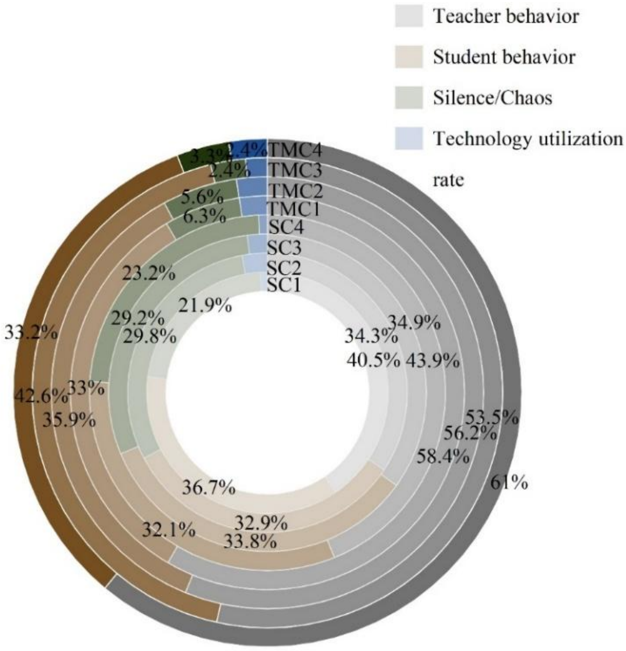

Figure 5. College English classroom interaction

4.1.2. Distribution of classroom interactions

Observation of teacher-student behavioral interactions using the adaptive classroom, teacher behaviors include lecturing, questioning, feedback or evaluation, prompting or instructing, acceptance and positive affect, individual instruction, boarding, visiting or monitoring, demonstrating, sharing, and moderating, as indicated using codes T1 to T11. Student behaviors included responding, discussing, initiating questions, reporting or sharing, evaluating, practicing, thinking, watching, practicing, demonstrating results, and making operational connections, indicated using codes S12 to S22. Figure 6 shows the behavioral coverage distribution of the five classroom samples, Sample 1~5, from the comprehensive distribution of behaviors, the behaviors that appear more in the adaptive English classroom are teacher's lecture (T1), questioning (T2), feedback or evaluation (T3), prompting or instruction (T4), and individual instruction (T6) Coverage rates are 15.127%, 7.082%, 7.082%, 7.082%, 8.551%, 10.24%, and 6.432%, and student responding (S12) and manipulative practice (S22), which were 4.871% and 19.826%, respectively. Among them, the overall mean of the coverage of students' operational practice behaviors is much higher than the teacher's lecture behaviors, indicating that the teacher spends more time organizing students' independent learning in the adaptive English learning classroom. Students' practice (S17) behaviors did not occur in any of the five samples, indicating that there are not many behaviors of traditional ways of classroom practice, such as practice with paper assignments, in the adaptive English learning classroom, which is mainly dominated by students' practice with media. Teacher's board (T7) behaviors were generally under-covered, indicating that teachers in adaptive English classrooms mostly present teaching content based on media technology.

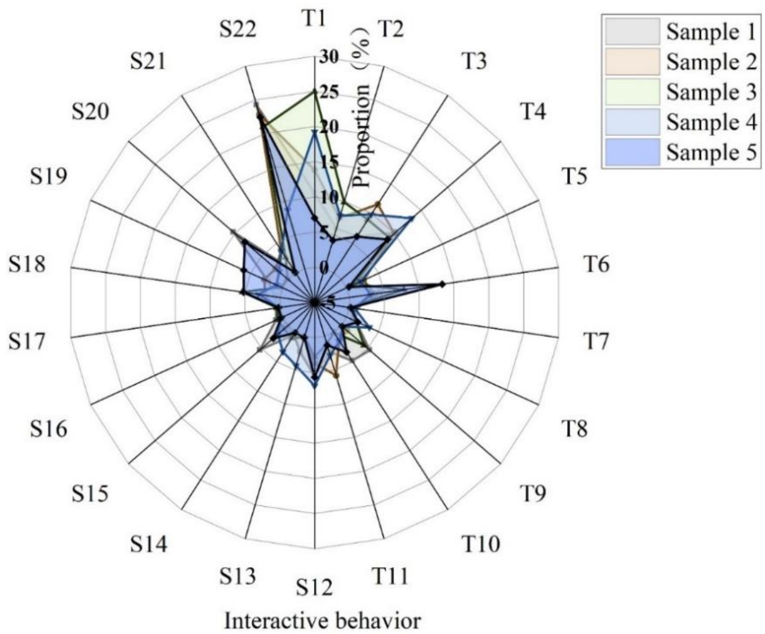

Figure 6. The behavior coverage distribution of class 5 classes

In terms of behavioral transitions, the behavioral transitions in the adaptive English classroom occurred centrally between the six behavioral modalities of T1, T2, T3, T4, S12, and S22. The transitions from teacher's question to student's response and from student's response to teacher's feedback or evaluation occurred throughout the whole classroom, and the behaviors of student's manipulative practice were mostly distributed in some parts of the classroom under the instruction of the teacher.

In terms of behavioral interactions, Figure 7 shows the distribution of behavioral interactions in the adaptive English classroom, and the distribution of classroom behavioral interactions from Sample 1 to Sample 5 is relatively consistent. In terms of classroom structure, the rate of teachers' verbal behavior and students' activity behavior are relatively high in adaptive English classrooms, with behavior rates of 42.487% and 32.529%, respectively, and verbal behavior is still the main way for teachers to impart knowledge to students. In terms of the distribution of the types of behavioral interactions, the adaptive English classroom is dominated by interactions between teachers and students and interactions between students and media technology, with relatively few student-student interaction behaviors and teacher-media interaction behaviors.

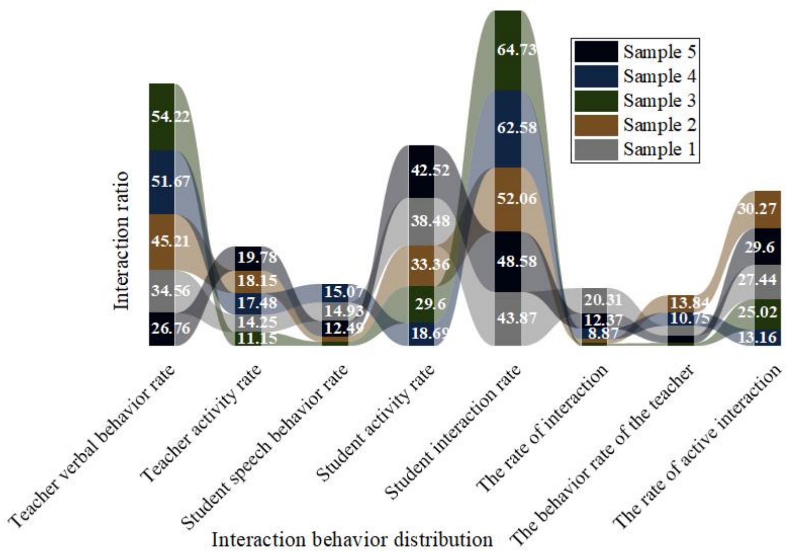

Figure 7. Adaptive distribution of adaptive English classroom behavior

4.2. Effectiveness of Teaching Feedback

4.2.1. Research Objectives

The empirical experiment was chosen to be conducted at the University of T. The university has relatively good facilities and the classrooms are equipped with interactive multimedia teaching devices such as whiteboards, tablet PCs, and teacher terminals, which support the use of the adaptive learning platform designed in this paper. Two lower grades (first year) and two upper grades (third year) of the university were assessed according to the feedback evaluation form for teaching English in colleges and universities. The two classes with no significant difference in assessment scores were identified as experimental subjects, each with 35 students.

4.2.2. Evaluation of teaching effectiveness

The evaluation of teaching effectiveness contains teaching process and teaching results. The evaluation of teaching process is mainly recorded and analyzed through classroom observation. The teaching results are mainly through compiling the English proficiency scale to compare the English scores of students in the experimental class with those of the control class, as well as the use of questionnaires as a post-class test of the experimental class students' attitudes and emotions toward the English classroom.

4.2.3. Experimental procedure

(1) Pre-test

The English proficiency of the students in the two classes was assessed in four aspects: listening, speaking, reading and writing, with assessment scores of 90 or more as excellent, 75-89 as good, 60-74 as average, and less than 60 as poor.

Questionnaires were administered to the experimental classes in order to find out the students' experience of the teacher's interactive classroom before the implementation of the Adaptive English Learning Platform in order to compare it with the effect of the classroom after the implementation of the strategy. Thirty-five questionnaires were distributed and 35 were recovered, with a recovery rate of 100%.

(2) Post-test

At the end of the experiment, the original assessment form was utilized to assess the English proficiency of the experimental class and the control class, and to compare the differences of each index between the two. At the same time, the original questionnaire was utilized to conduct classroom experience research for all the students in the experimental class, comparing the classroom interaction before and after the experiment as well as the changes in the students' experience.

4.3. Feedback on the effectiveness of interactive classroom teaching

4.3.1. Pre-testing

Before the experimental test, the teacher assessed each of the four selected classes, from which two classes with no significant difference in performance were identified as the experimental and control classes. The lower class 1 was selected as the experimental class and the upper class 2 as the control class, and Table 1 shows the homogeneity test of the pre-test between the experimental class and the control class. The above table shows that there is no significant difference between the two classes in the four indicators of listening, speaking, reading and writing respectively, and the p-value is greater than 0.05, which are homogeneous classes and can be used as research samples.

Table 1. Test the homogeneity test before the experiment class and the comparison class

Appraisal index	Class	N	Mean	S.D.	T value	P value	Conclusion
Listen	Experimental Class	35	79.266	5.648	0.915	0.348	Not significant
	Control class	35	77.845	6.415			
Say	Experimental Class	35	80.436	5.748	-1.065	0.309	Not significant
	Control class	35	82.148	6.735			
Read	Experimental Class	35	79.515	5.318	1.549	0.123	Not significant
	Control class	35	77.466	5.605			
Write	Experimental Class	35	80.718	5.198	0.248	0.748	Not significant
	Control class	35	80.469	4.848			

Table 2 shows the research on the attitudes of the experimental class before the use of the Adaptive English Learning Platform, and it is found that most of the students think that there is not enough positive and interactive atmosphere in the English classroom at present, and that there is not much interaction and communication, which is not effective in stimulating the students' interest in learning, e.g., 80% of the students think that there is not a lot of interaction between the teacher and the students, or between the students and the students, and 28.57% think that there is a positive and interactive classroom atmosphere in the English classroom at present. Meanwhile, more than 50% of the students recognized that teachers often encourage, perform or comment on students, indicating that teachers have realized that encouragement, praise and so on can enhance learning interest and help improve academic performance. In addition, the data show that many students are less willing to participate in various communication and discussion activities and do not like to take the initiative to speak or ask questions.

Table 2. The adaptive English learning platform is investigated by the previous experimental class

Serial number	Topic	Options	Percentage
1	Teachers can create a positive interactive classroom atmosphere	Generally and below	71.43%
		Identity and above	28.57%
2	There is a lot of interaction between teachers and students, students and students	Generally and below	80.00%
		Identity and above	20.00%
3	Teachers often encourage, praise, or comment on students	Generally and below	57.14%
		Identity and above	42.86%
4	The teacher often walks down the stage and walks into the student	Generally and below	85.71%
		Identity and above	14.29%
5	The current English class can arouse my interest in learning English	Generally and below	74.29%
		Identity and above	25.71%
6	I am very willing to speak or take my body temperature	Generally and below	57.14%
		Identity and above	42.86%
7	I like to participate in various exchanges and discussions	Generally and below	60.00%
		Identity and above	40.00%
8	I always actively participate in the group's activities	Generally and below	77.14%
		Identity and above	22.86%

4.3.2. Post-testing

Independent samples T-test was conducted on the differences between the experimental class and the control class in the post-test assessment data, and the test results are shown in Table 3.

Through data analysis, it can be seen that in terms of “listening” skills, the t-test probability of significance is $p=0.015<0.05$, indicating that the difference between the experimental class and the control class is significant, and the experimental class is better than the control class. In terms of “speaking” skills, the t-test probability of significance is $p=0.002<0.05$, indicating that there is a significant difference between the experimental class and the control class, and the experimental class is better than the control class. In terms of “reading” skills, the t-test probability of significance is $p=0.027$, indicating that there is a significant difference between the experimental class and the control class, and the experimental class is better than the control class. In terms of “writing” skills, the t-test probability of significance is $p=0.089>0.05$, indicating that the difference between the experimental class and the control class is not significant, but the mean value of the experimental class is higher than that of the control class, which indicates that the implementation of the strategy has helped students improve their “writing” skills.

Overall, after using Adaptive English Learning, students' English “listening, speaking and reading” skills are significantly improved, and it has a facilitating effect on students' “writing”.

Table 3. Independent sample t test

Appraisal index	Class	N	Mean	S.D.	T value	P value	Conclusion
Listen	Experimental Class	35	83.411	5.216	2.536	0.015	Significant
	Control class	35	79.254	6.248			
Say	Experimental Class	35	85.896	3.816	3.456	0.002	Significant
	Control class	35	81.594	4.628			
Read	Experimental Class	35	82.482	4.415	2.348	0.027	Significant
	Control class	35	79.712	5.626			
Write	Experimental Class	35	82.765	5.158	1.785	0.089	Not significant
	Control class	35	80.595	4.439			

After the experiment, the classroom experience research was re-conducted for all students in the experimental class. The research sent out 35 questionnaires and recovered 35 questionnaires, with a recovery rate of 100%. The comparison between the research situation and the pre-test research situation is shown in the following table.

Table 4 shows the comparison of the research situation before and after the implementation of the platform. By analyzing the data, it can be seen that after the implementation of the self-adaptation strategy, the classroom experience of the students changed significantly.

In terms of classroom interaction, 71.43% of students agreed with the statement "Teachers are always able to create a positive and interactive classroom atmosphere," an increase of 42.86 percentage points from the previous statement. 74.29% of the students felt that "there was a lot of teacher-student and student-student interaction." 80% of the students indicated that "Teachers often go off the podium and into the students". These changes show that students feel the equal, democratic and harmonious teacher-student relationship in the classroom and that teachers care about their students.

In terms of student participation in classroom interactions, there was a 20% increase in the number of students who said, "I am very willing to speak up or ask questions" compared to before the strategy was implemented. The number of students who said "I always take an active part in the group's common activities" also increased from 22.86% before the experiment to 51.43%. This shows that the implementation of the strategy helps to improve students' motivation and initiative in learning, and to develop students' ability to speak English and practice their ability to interact with others.

In terms of learning interest, more than half of the students are interested in the current English classroom, which is 31.43% more than before. More and more students like to participate in various communication and discussion activities, which indicates that the implementation of the Adaptive English Learning Platform, its classroom is welcomed by students and the teaching effect is significantly improved.

To sum up, it can be concluded through the comparison of the assessment data and the comparison before and after the classroom experience research that the application of the Adaptive English Learning Platform is able to create a positive and interactive classroom atmosphere, enhance the students' learning interest and academic performance, and realize the cultivation of students' quality.

Table 4. The comparison of the survey situation before and after the implementation

Serial number	Topic	Options	Pre-test proportion	Post-test proportion
1	Teachers can create a positive interactive classroom atmosphere	Generally and below	71.43%	28.57%
		Identity and above	28.57%	71.43%
2	There is a lot of interaction between teachers and students, students and students	Generally and below	80.00%	25.71%
		Identity and above	20.00%	74.29%
3	Teachers often encourage, praise, or comment on students	Generally and below	57.14%	22.86%
		Identity and above	42.86%	77.14%
4	The teacher often walks down the stage and walks into the student	Generally and below	85.71%	20.00%
		Identity and above	14.29%	80.00%
5	The current English class can arouse my interest in learning English	Generally and below	74.29%	42.86%
		Identity and above	25.71%	57.14%
6	I am very willing to speak or take my body temperature	Generally and below	57.14%	37.14%
		Identity and above	42.86%	62.86%
7	I like to participate in various exchanges and discussions	Generally and below	60.00%	42.86%
		Identity and above	40.00%	57.14%
8	I always actively participate in the group's activities	Generally and below	77.14%	48.57%
		Identity and above	22.86%	51.43%

5. Conclusion

This paper explores the adaptive learning mode supported by artificial intelligence technology, which forms a fuzzy neural network system by mixing fuzzy logic and artificial neural network, constituting an adaptive neuro-fuzzy system that constantly realizes self-adaptation by adjusting parameters. The system is used to construct an adaptive learning platform to carry out interactive teaching in the English classroom.

Using the teaching result feedback module of the adaptive platform, the interactive behavior matrix of English classroom is analyzed so as to evaluate the interactive teaching effect of English on the adaptive learning platform. In the English classroom of the adaptive learning platform, the rate of teachers' verbal behavior and students' activity behavior are relatively high, and the behavior rates are 42.487% and 32.529%, respectively.

Through the pre- and post-test experiments, an independent sample t-suggestion was taken on the assessment data of the experimental class and the control class to assess the teaching effect feedback. After using the adaptive platform for English learning, the probability of significance of students' English "listening, speaking and reading" ability is 0.015, 0.002 and 0.027 respectively, which are all less than 0.05, and the ability of these three aspects is significantly improved, while the "writing" aspect is promoted. The "writing" aspect has a facilitating effect.

Overall, the adaptive English learning platform constructed in this paper can create a positive interactive atmosphere, and at the same time improve students' English learning performance.

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